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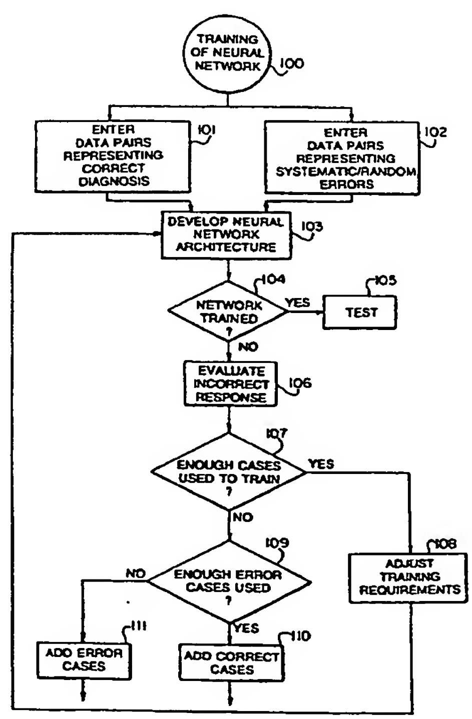
(54) Title: A SYSTEM FOR DIAGNOSING BIOLOGICAL ORGANS USING A NEURAL NETWORK THAT RECOGNIZES RANDOM INPUT ERROR

(57) Abstract

A system (1) for analysing the condition of biological organs is based on a set of parameters that have been identified as the factors that will determine the diagnosis of a particular organ. A neural network (4) is trained and used to analyse the values of these parameters as they relate to each other, and to first determine whether there is an error in the input data, and if not, then to generate a diagnosis from the analysis. In training the neural network (4), an initial set of training input/output pairs (101 and 102) are inputted into the neural network (4) that simulate parameters for correct diagnosis, and erroneous parameter combinations. The neural network (4), when presented with parameter data for making an actual diagnosis, is capable of either indicating that an error may have occurred in the measurements or test results obtained as input data, or correctly diagnosing the condition of the organ within a given tolerance level.



A SYSTEM FOR DIAGNOSING BIOLOGICAL ORGANS USING A NEURAL NETWORK THAT RECOGNIZES RANDOM INPUT ERROR

BACKGROUND OF THE INVENTION

1. Field of the Invention

The present invention relates to the application of neural networks for analyzing and/or diagnosing the condition of an object or function. In particular, a system of neural networks is used to not only analyze the object or function, but also to determine whether errors exist in the data used by the networks in their analyses.

In one specific application, the invention relates to a system that incorporates a neural network system for analyzing and diagnosing the condition of a biological organ or body function. The neural network system is designed to recognize the presence of error in measurement data from automated measuring devices or from manually-performed laboratory tests. A biological organ as used herein refers to any functional component in the body. Examples are the heart, the liver, and the kidneys. A body function is any chemical process or operation occurring in the body, such as blood flow, digestion, electrolyte production, and respiration, to name a few.

To diagnose the condition of an object or function, in particular a biological organ or body function, measurements are taken of their physical, chemical and/or physiological characteristics such as those described above. These measurements may be obtained using automated measuring devices, or manual laboratory techniques. Very often, however, such measurements require that a large number of samples be tested. Also, laboratories will conduct such measurements with samples from a large number of patients together. Further, the results of a large number of measurements may be analyzed by laboratory personnel together. As one may readily appreciate, the analysis of various measurements can be both highly complex and time consuming, especially

when measurements are taken and analyzed in large numbers. Various attempts to optimize the procedures for taking and analyzing measurements have often suggested the use of artificial or computer intelligence as a means of making such procedures more efficient. However, the question arises as to which type of computer intelligence should be used, i.e. expert systems, fuzzy logic systems, or neural networks?

Among the advantages offered by neural networks, they are particularly capable in using known information to draw conclusions about things that are similar to but not exactly like the known information. Analyses that require generalizations, the understanding of subtle relationships, and the processing of large amounts of data are among the applications to which neural networks are well-suited.

When analyzing complex objects and functions, such as organs and body functions, a large numbers of factors can affect the condition of the organ or body function. The relationships between these various factors or parameters are very complex, and often very subtle. Consequently, neural networks such as those incorporated into the present invention are uniquely suited to the type of analysis conducted by the invention.

2. Related Art

The application of neural networks has increased dramatically since the 1950s when neural networks were first conceived as a form of computer intelligence. Today, neural networks are used in numerous fields including financial forecasting, business decision making, pattern/character recognition, mechanical controls, and medical diagnosis.

Neural networks as they are known today consist of a plurality of artificial or simulated neurons that are interconnected to one another. Each neuron generally consists of a number of inputs that enter a summation and transfer element which then generates an output based on the inputs received. Each neuron is connected to other neurons in

order to either receive inputs from or output data to other neurons. This interconnection between neurons is generally organized in at least three layers. An input layer receives the information that the network will use to generate an answer. The output layer produces the final answer. A hidden intermediate layer associates and connects the input layer with the output layer.

The architecture of a neural network is developed through training in which different sets of data inputs and their associated known outputs are used to generate the mathematical models for the connections between neurons. Details on the development of a neural network's architecture as known in the art are discussed in the publication Introduction to Neural Networks: Design, Theory and Applications, J. Lawrence, California Scientific Software Press, Nevada City, CA 1994. This publication is incorporated herein by reference.

As is known in the prior art, when training a neural network, error conditions occur when a neural network fails to output the correct answer in response to a given set of known parameters. Conventionally, such error conditions are regarded as being caused by a lack of sufficient input examples during the training of the network. The conventional solution then is to input additional data inputs and outputs to further train the network. The rationale is that the additional data inputs and outputs will train the network to refine its ability to analyze a given set of data, and thereby avoid those same error conditions in the future. To date, the error associated with neural network operations involved the minimization of incorrect responses by the network during the training process.

However, the training of neural networks does not prepare the networks to recognize or compensate for errors that may be incorporated into the data that the networks analyze. Rather, conventional neural networks simply output erroneous answers based on the input data. However, to date, no conventional neural network has ever been designed or trained to recognize errors in the input data.

There are two major classifications of error that may occur in the data: systematic error and random error. Systematic errors are frequently related to improper design or adjustment of measurement apparatus; such errors reduce accuracy by systematically skewing or offsetting the observed data. Analysis of a known quality (called a "standard") by this apparatus can reveal the nature of the error, and accuracy can be regained by adjusting the apparatus or applying some correction. In contrast, random errors result from insufficiently controlled variations in measurement conditions. Careful consideration of the conditions of measurement can substantially reduce random errors, but unlike systematic errors, random errors cannot be eliminated, nor can some formula be derived to correct an observation influenced by such errors.

The prior art involving the determination of random error involves the interpretation of repeated measurements and/or observations of single quantity. By conducting multiple measurements of a single quantity, a range of values randomly scattered around a true value will be obtained. This data set involving a single measured quantity is amenable to statistical treatment in order to determine the presence of random error in some or all of the measured values comprising the data set.

The prior art does not allow for the determination of random error in a single measured value, but rather relies on the statistical analysis of repeated determinations of a single quantity. In determining random error, one currently constructs a plot or graph of all measurements or observations taken of such a single quantity. Conceptually, the plotted measurements or observations form a "population" of data that is used to construct a histogram, also called a frequency diagram or frequency distribution. The histogram shows the frequency with which a particular value or range of values is obtained versus the scale of all values obtained for a single quantity. The shape of this curve is known as a "normal" or "Gaussian" distribution for this quantity. The curve is defined by the average of the values (the "central tendency") and the range of these values (the "dispersion"). The most useful measurement of dispersion is given by a quantity known as the "variance". After constructing such a mathematical curve, one is able to determine

the probability that a subsequent measurement of that value is contaminated by random error by comparing that measurement to the graph. If the measurement falls within the range of the plotted points (as defined by the central tendency and the variance), it is determined to be a valid measurement. If, on the other hand, the measurement falls outside the range of plotted points, it is considered to be erroneous. Thus, it is evident that the prior art requires multiple measurements of a single quantity in order to statistically determined the probability of random error contamination. The present invention is directed to overcoming the deficiencies of the prior art as described above.

SUMMARY OF THE INVENTION

The present invention is generally directed to a system using a neural network to analyze parameter data that describes the condition of an object or system being studied. The neural network is designed and trained to recognize systematic and random errors that may occur when the parameter data is obtained. By recognizing systematic and random errors, steps can be taken to eliminate the error and correct the parameter data. It is this ability to recognize error, both systematic and random, which distinguishes the present invention from all previously existing methods and systems, as will be discussed below.

The present invention in a specific embodiment is directed to a system for analyzing the condition of biological organs based on a set of parameters that have been identified as physiologically related factors that will determine a diagnosis involving a particular organ. A neural network is trained and used to analyze the values of these parameters as they relate to each other, and to first determine whether there is an error in the input data, and if not, then to generate a diagnosis from its analysis.

In training the neural network, an initial set of training data, consisting of a set of values representing parameter data and a corresponding output answer, is inputted into the neural network. Hereinafter, each set of parameter data and its corresponding output answer will be referred to as an input/output data pair. This set of training input/output

data pairs includes input/output data pairs having combinations of values for the parameters that will generate the different types of diagnoses associated with any one organ. Specifically, each input/output data pair consists of parameter values (or inputs) that together result in a given diagnosis (or output). In addition, this training set includes input/output data pairs of parameter values that are designed to simulate input data errors. Such errors include, for example, an incorrect temperature reading, improper test sample identity (i.e., patient sample mix-up), a miscalibrated measuring/testing instrument, or a contaminated test sample.

To simulate such error conditions, one or more of the parameter values in a given input/output data pair may be set above or below the range of values possible for those parameters. Alternatively, one or more parameter values in an error input/output data pair may be set to values that are clearly erroneous relative to the other parameter values in that error input/output data pair. The outputs of such error input/output data pairs all designate "ERROR."

By training the neural network with input/output data pairs that not only simulate parameters for correct diagnoses, but also those that simulate erroneous parameter combinations, the neural network, when presented with parameter data for making an actual diagnosis, becomes capable of either indicating that an error may have occurred in the testing of the organ or correctly diagnosing the condition of the organ within a given tolerance level. In particular, given a set of parameter data, the neural network can either output an indication of whether the parameter data is "correct", i.e. all parameter values represent accurately obtained measurements or test results, or "corrupted," i.e. containing at least one parameter that is erroneous.

In another embodiment, the neural network can, as above, output either a diagnosis of the condition of the organ whose parameter values are being analyzed, or again output an indication that the parameter data is corrupted, but then, when the neural network concludes that an error exists among the parameter data, the system can proceed to initiate an analysis to isolate and identify the parameter(s) that is the source of the error. One

method for analyzing the parameter data is to generate different versions of the neural network for the particular organ, but with one or more parameters less than the original neural network associated with that organ. The different neural networks then each conduct their own analysis of the input data, but based on their more limited sets of parameters. As long as the erroneous parameter or parameters are part of any neural network's consideration, its output or answer will be "ERROR." However, once a network analyzes the input data without considering the erroneous parameter(s), then that network will output a diagnosis other than "ERROR." Based on this method of deductive reasoning or analysis, the system can identify which parameter or parameters are erroneous.

In contrast to the prior art discussed above, the present invention is capable of identifying erroneous input data without merely comparing the data to an expected range. Rather, a novel aspect of the present invention is its ability to detect the probability of random error contamination in a measurement from a single measurement and/or observation without the need to construct a normal or Gaussian distribution of the data.

By having identified which parameter or parameters are erroneous, the present invention allows a user to take corrective action specific to the erroneous parameter or parameters. As one can appreciate, without the use of the invention described herein, further analysis of a few or even one parameter to simply determine the source of error, such as analyzing the measuring equipment that generated those parameters, the conditions under which the measurements of the parameters were made, and/or the test samples from which the parameters were derived, can be complex and time-consuming. The actual corrective actions to eliminate the errors such as repeating the tests or measurements, recalibrating and/or repairing faulty instruments, instituting measures to prevent corruption or decaying of the test samples, changing current procedures that cause the error(s), and developing new procedures that avoid the error(s) can be as complex and time-consuming, if not more so. With the present invention, instead of having to analyze every parameter to determine the source of error, the user can focus any further analysis

to the erroneous parameter(s), thereby optimizing the time, effort and expense put to correcting the error.

BRIEF DESCRIPTION OF THE DRAWINGS

The invention is better understood by reading the following Detailed Description of the Preferred Embodiments with reference to the accompanying drawing figures, in which like reference numerals refer to like elements throughout, and in which:

Figure 1A shows a general block diagram of the system for implementing the first and second embodiments of the present invention;

Figure 1B shows a general block diagram of the components of the central data processing device of the present invention;

Figure 1C shows a general block diagram of the components of the neural network system of the present invention;

Figure 2 shows a flowchart-style diagram illustrating the training of the neural networks to recognize parameters for both correct diagnoses and error conditions;

Figure 3 shows a flowchart-style diagram illustrating a routine for testing the neural networks of the present invention;

Figure 4A shows a flowchart-style diagram illustrating the general operation of the neural network of the present invention according to a first embodiment thereof;

Figure 4B shows a flowchart-style diagram illustrating the general operation of the neural network including the process for identifying the source of an error condition determined by the neural network according to a second embodiment of the present invention;

Figure 5 shows a general block diagram of the system for implementing a third embodiment of the present invention;

Figure 6 shows a general block diagram of the system for implementing a fourth embodiment of the present invention;

Figure 7A shows a general block diagram of the system for implementing a fifth embodiment of the present invention;

Figure 7B shows a general block diagram of the system for implementing a variation of the fifth embodiment of the present invention;

Figure 8A shows a general block diagram of the system for implementing a sixth embodiment of the present invention; and

Figure 8B shows a general block diagram of the system for implementing a variation of the sixth embodiment of the present invention.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

In describing preferred embodiments of the present invention illustrated in the drawings, specific terminology is employed for the sake of clarity. However, the invention is not intended to be limited to the specific terminology so selected, and it is to be understood that each specific element includes all technical equivalents which operate in a similar manner to accomplish a similar purpose.

First Embodiment

As shown in Figure 1A, the present invention is implemented in a system 1 that incorporates a central data processing device 3 connected to a plurality of automated measuring instruments 2. The central data processing device 3 is implemented either through a mainframe computer such as an IBM AS/400, or a network server computer using, for example, an IBM-compatible computer that has an Intel Pentium processor. Within the central data processing device 3 as shown in Figure 1B, measurement data generated by the measuring instruments is received by a central processing unit 7 that can then store the measurement data in a data memory bank 8. The data memory bank 8 is embodied primarily as storage space on a non-volatile memory device that can be written into, such as a hard disk or magnetic tape. By using a non-volatile memory device, measurement data can be stored over an extended period of time, allowing the use of the

measurement data in an analysis that is repeated several times over or in several different analyses.

The central processing unit 7 can also access other data memory banks 9 for additional data that may be applicable. Such information would include patient hospital records, test data from prior measurements and tests, measurement data for other diagnosis for the same patient, and calculations of parameters derived from other measurement data. The other data memory banks 9 are also embodied in a non-volatile memory device, such as a hard disk or magnetic tape. However, since data in the data memory banks 9 can include patient hospital records or other valuable information, the data memory banks 9 can include non-volatile memory devices, i.e. hard disks or magnetic tapes, that are protected by limited access procedures or that cannot be overwritten. An example of a memory device that cannot be overwritten is a CD-ROM.

The measuring instruments 2 are used to conduct automated laboratory tests on analytes related to a biological organ or body function. As noted above, the measuring instruments 2 then generate measurement data based on the laboratory tests conducted. The measurement data is inputted into the central data processing device 3. The number I of measuring instruments 2 is determined by the number and types of parameters being measured or tested.

For example, if the present invention were applied in the medical field to the diagnosis and analysis of thyroid function, the measuring instruments 2 would be used to measure the level of the thyroid stimulating hormone (TSH), the level of total thyroxine (T4), the level of free thyroxine (T4 Free), the level of triiodothyronine (T3) and the level of triiodothyronine uptake (T3 Uptake), and to determine the free thyroxine index (FTI) based on the level of the total thyroxine (T4) and the level of triiodothyronine uptake (T3 Uptake). Examples of measuring instruments 2 for performing such tests include a Dade Stratus IIntellect device, a DPC "Coat-A-Count" RIA assay, a DCP Immulite device, an ABBOTT Axiom-IMx device, a BAYER Immuno I device, Behring Opus-Opus Plus-Magnum device, a Corning ACS 180 device, A Boehringer Mannheim ES-300 device, a

TOSOH AIA 600, 1200 device, and a Hybritech Photon ERA device. These devices are examples of radioimmunoassay and enzymeimmunoassay systems for analyzing thyroid functions. The Dade Stratus IIntellect device can measure the TSH, T4, T3 and T3 Uptake levels, and calculate the FTI. The DPC "Coat-A-Count" RIA assay is used to measure the Free T4 level. All the other devices listed above are all capable of measuring the TSH, T4, Free T4, T3, and T3 Uptake levels, and calculating the FTI.

Measurement data is also inputted into the central data processing device 3 using a manual input terminal 6. The manual input terminal 6 is embodied in a terminal connected to the central data processing device 3 when implemented as a mainframe computer, or in a stand-alone computer (i.e., an IBM-compatible personal computer) networked with the central data processing device 3 when implemented as a network server. The manual input terminal 6 can even be implemented in a portable or laptop computer that communicates with the central data processing device 3 through a modem or a dedicated network docking port. The manual input terminal 6 is intended to allow a user to input measurement data derived from having conducted measurements in a laboratory or in a remote location away from the central data processing device 3 using measuring instruments or non-automated test equipment not connected with the central data processing device 3.

The central processing device 3 incorporates interface devices 10 for interfacing with the various measuring instruments 2. Automated measuring instruments 2, such as those specifically listed above, will output data signals using signal communication formats initially selected by the manufacturer, for example, ASCII format. The interface devices 10 translate the data signals from the measuring instruments 2 into a form usable by the central data processing device 3. One example of an interface device is a Beckman Synchron CX4CE/CX7 system that is used to interface the central data processing device 3 with a measuring instrument 2 using RS-232-C interface hardware and X-ON, X-OFF communication protocols. Another example is the software-implemented ILS-5 Laboratory System by Dynamic Healthcare Technologies, Inc. The

ILS-5 system interfaces a mainframe computer, e.g. an IBM AS/400, with the various automated measuring instruments.

Also as shown in Figure 1A, a neural network system 4 is connected to the central data processing device 3. The central data processing device 3 communicates with the neural network system 4 by providing the measurement data for the neural network system 4. Within the central data processing device 3, the central processing unit 7 can either access and output the measurement data directly from the data memory banks 8, or process the measurement data into parameter data that is in a form usable by the neural network system 4. The central data processing device 3 can also calculate other parameter data from the measurement data for the neural network system 4. In the example of the measurements used for diagnosing a thyroid condition, the FTI is calculated as follows:

$$(T4 * T3\ Uptake) = FTI$$

The neural network system 4 receives the measurement data, and processes that data in accordance with its specific design and training, and the specific application selected. The neural network system 4 itself is the implementation of several sets of neural networks. Each set of networks is designed to analyze a specific biological organ or body function. Each neural network in a set is designed to analyze the same data on the biological organ or body function, except in a slightly different manner from each other. For example, in addition to the thyroid, other body organs and/or functions can be analyzed using a set of neural networks so designed. Among such other body organs are the liver, the kidney, tumors, and the heart. Examples of body functions are electrolytes, blood gases and fertility.

When a specific organ or body function is selected, for example the thyroid, a neural network system 4 consisting of neural networks designed to analyze the thyroid are used to process the measurement data obtained from the measuring instruments 2. The measurement data is inputted into the neural network system 4, and then the network

system 4 outputs signals indicating its diagnosis or answer. The signals on the diagnosis of the neural network system 4 are sent to an output or display device 5.

Implementation of the First Embodiment

In the preferred embodiments of the present invention, the neural network system 4 is implemented as a set of computer-simulated networks generated using a neural network simulation software tool, for example, "BrainMaker," Version 3.1 by California Scientific Software. The neural network system 4 can also be implemented as a series of hard-wired neural networks. For practical reasons, the computer-simulated implementation of the neural network system 4 is preferred.

The neural network system 4 shown in Figure 1C consists of several neural network versions 4a. When the neural network system 4 is implemented as a set of computer-simulated networks, the neural network system 4 is embodied in a computer or other data processing device, such as an IBM-compatible personal computer. As a computer or data processing device, the neural network system 4 can be implemented as a stand-alone unit separate from the central data processing device 3, or as part of the central data processing device 3 itself, i.e. a software or hardware module thereof. Consequently, actual operation of the neural network system 4 can be controlled through that computer using an operator interface 11. The operator interface 11 is embodied in the computer's terminal that includes a keyboard and a display. The display of the operator interface 11 can serve as the output device 5 of Figure 1A.

The number X of neural network versions 4a is based on the number of characteristics measured by the all measuring instruments 2 and by non-automated tests that are reported to the central data processing device 3 through the manual input terminal 6. First, for any one particular biological organ or body function being examined, there will be a first neural network version 4a that analyzes the biological organ or body function using every identified characteristic or parameter. That number N of identified characteristics or parameters, hereinafter referred to as "parameters," constitutes the

maximum number of parameters for that biological organ or body function. All other network versions 4a after the first network version will be designed to analyze the biological organ or body function using subsets of the maximum number N. The subsets are permutations of the different parameters with the number of parameters being less than the maximum number of parameters N.

For example, if six parameters such as those for analyzing thyroid functions are identified as the maximum number N = 6, the additional network versions would include versions using different permutations of parameters less than six. Specifically, additional network versions include those using permutations of five of the maximum six parameters, permutations of four of the maximum six parameters, permutations of three, etc. Table 1 shows examples of some of the permutations of parameters for several of the network versions for analyzing a thyroid. In Table 1, the symbol "Used" designates that the parameter is used by the network version; the symbol "*" indicates that the parameter is not used. As shown, the first network version uses all six of the parameters TSH, T4, Free T4, T3, T3 Uptake and FTI. A second network version uses five of the six parameters -- T4, Free T4, T3, T3 Uptake and FTI; while a third network version uses five different parameters -- TSH, Free T4, T3, T3 Uptake and FTI. Additional network versions are created using permutations of progressively fewer parameters. In this example of the parameters for diagnosing a thyroid condition, a total of 121 network versions are generated using all permutations of the six original parameters.

By having generated every permutation of the network versions, it is possible to analyze the desired biological organ or body function with less than the maximum number of parameters. Among the reasons for analyzing the biological organ or body function with fewer than the maximum number of parameters N are (1) the idea of analyzing which parameters may be the source of an error in the measurement data, and (2) the practical limits to which a biological organ or body function can be measured. The analysis and detection of error will be explained in further detail below. An example of a "practical requirement" that will demand the analysis of an object with less than the

maximum number of parameters is illustrated by a medical application of the present invention.

As is known to those skilled in the art, when a patient needs an analysis or diagnosis for a particular organ or body function, many if not most physicians will not have every single test available for that organ or function taken. Rather, the physician will have one, two or even three such tests done depending on the individual patient's circumstances. All available tests would likely be conducted only when the patient's condition mandates a battery of available tests. Consequently, the amount of parameter data on the organ or body function to be diagnosed will in many circumstances be limited to less than the maximum number of parameters identified for that organ of body function. Therefore, by having generated all network version permutations, the neural network system 4 of the present invention can produce viable diagnoses even when measurement data on the biological organ or body function is limited.

Each set of neural networks for analyzing a specific biological organ or body function is generated by training each of the neural network versions in the set. Techniques for the training and development of each neural network are described in the previously identified publication <u>Introduction to Neural Networks: Design, Theory and Applications</u> to J. Lawrence.

<u>Training of a Neural Network - In General</u>

In the training of each neural network, different sets of parameter input data and their corresponding output answers are inputted into a neural network. The neural network is then allowed to develop the necessary internal architecture based on those sets of parameter data. An initial set of training input/output data pairs is developed. This set of training input/output data pairs uses selected parameter values that together translate into predetermined outputs. One way of generating the training set is to use values for each of the parameters that are considered within normal ranges for those parameters at

a given output. More specifically, data pairs can be generated using permutations of the different parameters within their normal ranges.

For example, in diagnosing thyroids, for a euthyroid condition, the normal value range of T4 is 5-12 µg/dl (micrograms per decaliter), while the normal value range of T3 is 100-200 ng/dl (nanograms per decaliter). Several data pairs can be generated where T4 is set at a value within its normal range (e.g., 5 µg/dl) in combination with selected values for T3 within its normal range. Another set of data pairs would have T4 set at another value within its normal range (e.g., 6 µg/dl) again in combination with selected values for T3 with its normal range. Further sets of data pairs can be generated using similar permutations and combinations of the TSH, T4, Free T4, T3, T3 Uptake, and FTI parameters with corresponding indications of either a euthyroid, hyperthyroid or hypothyroid condition as their outputs.

An alternative method for generating an initial training set would be to use parameter values and corresponding outputs from actual cases. In this method, data pairs representing the euthyroid, hyperthyroid and hypothyroid conditions can be easily be provided.

As shown in Figure 2, the process of training a neural network (Process 100) includes the inputting of the training set of input/output data pairs. There are, as shown, two types of input/output data pairs: those that will output a correct diagnosis (Step 101), and those that will output an error condition (Step 102). As noted above, the data pairs with correct diagnoses can be obtained by either generating different combinations and permutations of parameter values or by using parameter values form actual cases. Example values for input/output data pairs used in analyzing a thyroid condition are shown in Table 2. As shown, twenty-five input/output data pairs for correct diagnoses were generated for training a neural network, where nine data pairs indicated the euthyroid condition, eight data pairs indicated the hyperthyroid condition, and eight data pairs indicated the hypothyroid condition.

Permutations of input/output data pairs can also be used to generate different combinations of the TSH, T4, Free T4, T3, T3 Uptake, and FTI parameters that have corresponding indications of "ERROR" as the output. Similarly, actual cases of data pairs that would indicate "ERROR" can be used. In Table 2, input/output data pairs indicating "ERROR" constituted an additional twenty-five data pairs for training the network.

When training the neural network, as a general rule, the total number of input/output data pairs for training should initially be divided in approximately equal numbers between the different types of outputs possible. For neural networks having four types of outputs, i.e. euthyroid, hyperthyroid, hypothyroid and ERROR, 10-15 input/output data pairs for each type of output, for a total of 40-60 data pairs, has been found to produce optimal results. However, as evident from Table 2, the initial number of data pairs will vary as required by the training of the neural network.

As indicated in Step 103, the initial set of data pairs is inputted to develop and train the neural network architecture. Specifically, the neural network begins connecting and weighting its input, output and hidden neurons based on the inputted data pairs. This process of connecting and weighting of neurons constitutes the development of the network's architecture. The training and development of each neural network in this manner is consistent with techniques for developing neural network architectures as known in the art.

When the neural network completes this initial development of its architecture, the network stops and a determination is made whether the network is fully trained (Step 104). The operation of the neural network, i.e. its ability to output an expected answer using the training set of input/output data pairs, is evaluated by inputting the training set into the neural network as if the neural network is analyzing parameter values for an actual case. If the network outputs all the expected answers, then the network is tested using a set of non-training input/output data pairs (Step 105).

If the network instead fails to output all the expected answers, then the training process evaluates the incorrect responses of the network (Step 106). Specifically, the data

pairs that the network analyzed incorrectly are identified, and then analyzed to determine what are the common characteristics of those data pairs. For example, if the network incorrectly analyzed all data pairs having outputs indicating a euthyroid condition, this means that the network does not yet fully comprehend the conditions that will result in the euthyroid condition. This further indicates that not enough cases were used in the initial training set (Step 107).

In the example, the network is deficient in analyzing the euthyroid condition. Therefore, at Step 109, the training process proceeds to Step 110, where additional data pairs that indicate the euthyroid condition are added to the training set. If, on the other hand, the network was deficient in analyzing the "ERROR" condition, then at Step 111, additional data pairs indicating the "ERROR" condition are added. The exact number of data pairs to be added and/or the values of the parameters in the data pairs to be added to the training set is the number required to train the network, as further illustrated below.

Specifically, if the network fails to analyze any of the data pairs indicating a euthyroid condition correctly, then for example, enough data pairs may be added to sharply increase the total number of such data pairs in the training set (e.g., double, triple). Alternatively, a smaller number of data pairs with parameter values more representative of the euthyroid condition may be selected instead. As one of ordinary skill in the art will appreciate, there is no exact formula for how to change the training set of data pairs. Rather, a thorough understanding of the neural network's progress in training, and even trial and error, will most likely guide the user on how to correct the network.

In another example, if the network incorrectly analyzes only a subset of the data pairs that indicate a euthyroid condition, and that have parameter values close to or common with one another, then this indicates that the number of data pairs in the training set is sufficient. Instead, the training requirements imposed on the network will require adjustment. For example, the range of values that the network is allowed to consider for

a particular parameter can be truncated. The amount of time that the network is given for analyzing a data pair can be increased so that the network can better analyze the data pair. Also, the order in which the data pairs in the training set are presented to the network can be randomized, to discourage the network from relying on the order of the data pairs as a means for analyzing the data pairs.

After the training requirements are adjusted or further input/output data pairs are added (Steps 108, 110 or 111), additional training takes place and the neural network architecture is again developed (Step 103).

If Step 105 for testing is initiated instead of the incorrect response evaluation (Step 106), then as shown in Figure 3, the process for testing the neural network (Process 200) incorporates the step of inputting a non-training set of input/output data pairs into the network (Steps 201, 202). Like the training set, the data pairs in this set have predetermined outputs. Those predetermined outputs are compared with the actual analyses of the network. If the network correctly analyzes all the data pairs, then training is considered complete, and the neural network can be applied to analyzing input of actual cases (Step 205). Otherwise, if the network fails to analyze all the data pairs correctly, then the network must be re-trained (Step 204). Re-training of the network is a repeat of the initial training process of the network as illustrated in Figure 2. Unlike the initial training process, the training set must be modified by adding new data pairs, and/or the training requirements must be adjusted as was done in Step 108.

Training of Each Neural Network - Error Recognition

A main feature of the present invention is the use of input/output data pairs that have outputs indicating "ERROR." Unlike the prior art, the use of input/output data pairs indicating error conditions is not intended to train the network to avoid outputting incorrect diagnoses. Rather, the use of error condition input/output data pairs allows the neural network to detect the presence of errors in the parameter data being inputted.

Input/output data pairs for indicating "ERROR" are used to simulate both the systematic and random errors that may occur when measurements are taken or when tests are conducted. Random errors include an incorrect reading of an instrument by a technician, contaminated test samples, or decayed test samples. Examples of systematic errors include too few test samples taken, and miscalibrated measuring/testing instruments.

When generating input/output data pairs for training the network, such as those illustrated in Table 2, the data pairs for indicating "ERROR" are derived from setting at least one parameter in each such data pair at an incorrect value. Such incorrect values include those that are too high or too low for the specific parameter, or those that are outside the range of values possible for that parameter relative to the value of another related parameter. For example, as discussed above, the number of triiodothyronine (T3) molecules present is directly related to the level of total thyroxine (T4) molecules present. An example for an input/output data pair for indicating "ERROR" would have T3 set at a value that was inconsistent with the value of T4.

<u>General Operation of the System</u>

In order to train a neural network to recognize these error conditions, sufficient numbers of input/output data pairs should be generated simulating as many systematic and random errors as can be identified. The exact number of such data pairs will depend on the specific biological organ or body function to be analyzed

In the general operation of the system of the present invention, data streams from measuring instruments 2 are inputted into the central data processing device 3 (See Figure 1A). The data streams are translated into data usable by the central data processing device 3 by the interface devices 10 (See Figure 1B). As explained above, the central processing unit 7 stores the data in a measurement data memory bank 8 directly, or manipulates that data into parameter data usable by the neural network system 4. The central processing unit 7 also calculates and derives other parameter data from the data

received from the measuring instruments 2. For example, measurements and testing of the TSH, T4, T3, T3 Uptake parameters are made by a Dade Stratus IIntellect device, while the Free T4 parameter is measured by a DCP "Coat-A-Count" RIA assay. The free thyroxine index (FTI) as known in the art is calculated from the above parameters.

Figure 4A illustrates the process of the neural network (Process 300) of the present invention in the first embodiment. As shown, input data of an actual case are inputted into and processed by the trained network (Process 301, Step 302). The network then generates an output based on the inputted parameters (Process 303). In the process of generating the output, a determination is made whether the output is an indication of "ERROR" or a diagnosis (Step 304). If the output is an analysis of the biological organ or body function, then it is reported (Step 305) through an output device 5 (See Figure 1A). Some examples of an output device 5 include a display on a computer terminal (See Figure 1C, Reference 11), a paper printout, or an alarm.

If the output is an indication of "ERROR," then in the first embodiment of the invention as shown in Figure 4A, the error condition is reported (Step 306). The error is reported through the output device 5.

Second Embodiment of the Invention

In a second embodiment as shown in Figure 4B, the reporting of an error condition initiates a process of analysis to determine which parameter or parameters are the source of the error (Process 307). In this process of determining the source of error, the parameter data from the actual case is divided into subsets based on the various types of network versions available for analyzing that organ or function (Step 308). For example, Table 1 illustrates 10 permutations of a possible 121 permutations of subsets using the parameters for the analysis of thyroid conditions for determining the subsets. As shown, an "ERROR" indication results when the neural network using all six parameters TSH, T4, Free T4, T3, T3 Uptake and FTI (Network Version 1) is used to

analyze an actual case. For purpose of this example, only Network Versions 2 through 7 will be used to determine the source of error in the measurement data. As shown in Table 1, Network Versions 2 through 7 differ from each other by one parameter. Specifically, Network Version 2 uses the T4, Free T4, T3, T3 Uptake and FTI parameters, while Network Version 3 uses the TSH, Free T4, T3, T3 Uptake and FTI parameters, etc. Consequently, subsets of the parameter data from the actual case are derived based on the groupings used by Network Versions 2 through 7.

Each of the subsets of parameter data is then applied in a Process 309 in which the subsets are inputted into and processed by the appropriate network versions that use a particular subset. Each network version subsequently generates an output (Step 310). The outputs from all the network versions are then compared with one another to determine the parameter or parameters that are erroneous (Step 311).

Specifically, if network versions, for example Network Versions 2 and 4 through 7, in their analyses each output "ERROR," then the erroneous parameter or parameters are among those used by those network versions. On the other hand, if a network version, for example Network Version 3, outputs an analysis other than "ERROR," then the erroneous parameter(s) was not among those use by Network Version 3. In this case, the erroneous parameter is T4. By this deductive analysis, the system identifies which parameter or parameters are erroneous, and indicates the source of error that caused the "ERROR" indication in the initial analysis (Step 312).

For purposes of determining which parameter or parameters are erroneous, the number of parameters used in any of the network versions is expressed as follows:

$(N - m)$ where m is the number of parameters not considered and

$m \geq 1$

As noted above and illustrated in Table 1, the network versions other than Network Version 1, will all use combinations of parameters less than the maximum number N. That number of parameters for practical purposes should not be less than two ($(N - m) \geq 2$). If $N = 2$, there is only be one degree of freedom in generating network

versions of (N - m) = 1. Either the first or second parameter would be eliminated in a network version. However, a neural network cannot generate its architecture with only one parameter. At least two parameters are required to generate a viable neural network architecture. Consequently, if N = 2, then effectively there would be no network versions that could be used to determine which of the two parameters is erroneous. At best, the neural network system 4 outputting an "ERROR" indication in analyzing N = 2 parameters would simply stop at indicating that an error exists in at least one of the two parameters.

In order to determine the source of an error, the maximum number of parameters N for a given biological organ or body function should not be less than three ($N \geq 3$). At N = 3, there are two degrees of freedom in generating network versions of the neural network. In other words, combinations of the first parameter with the second parameter, the first parameter with the third parameter, and the second parameter with the third parameter would constitute three network versions, in addition to the version using N=3 parameters. If parameter data were applied to all three network versions, then there exists a minimum possibility of being able to determine which parameter was erroneous. For example, if only the first parameter is erroneous, then the two network versions using the first parameter would output "ERROR." The network version using the second and third parameters would output an analysis other than "ERROR," indicating that the first parameter was erroneous.

In addition to the above examples of network versions that used only one less parameter than the maximum number N, other network versions can be generated with combinations of two or more parameters are removed from consideration. These other network versions are based on removing parameters that are inter-related or affect each other's values. Specifically, some parameters are either directly related to other parameters. Some parameters may even be directly derived from other parameters. For example, in many applications and technologies, temperature is proportional to pressure, weight is proportional to mass, and velocity is proportional to acceleration. Parameters

such as those described are so related that when one parameter is removed from consideration, the presence or absence of other related parameters does not affect the overall analysis.

When several parameters that are so related exist, network versions can be generated that have all such parameters removed together from consideration. Again using as an example the analysis of thyroid conditions, the number of triiodothyronine (T3) molecules present is related to the level of total thyroxine (T4) molecules present. Specifically, the majority of triiodothyronine molecules are produced by the existence of thyroxine molecules. Therefore, one network version 4a (See Figure 1C) has the T3 and T4 parameters removed; that particular network version 4a only considers the parameters of the thyroid stimulating hormone (TSH), the measurement of free thyroxine (T4 Free), the measurement triiodothyronine uptake (T3 Uptake), and the test for the free thyroxine index (FTI).

Other combinations of parameters can be used to develop other network versions so long as the eliminated parameters are selected based on their inter-relationship with one another, and with the requirements of the analysis being conducted as would be known to one of ordinary skill in the art.

Third Embodiment

In the embodiments described above, the neural network system 4 is described as being implemented, among other ways, as a computer or data processing system either separate from or integral with the central data processing device 3. In the above embodiments, the data from the measuring instruments 2 are inputted into the central data processing device 3 for storage or further processing for the neural network system 4. In an alternative third embodiment of the invention as shown in Figure 5, each of the measuring instruments 2 is connected to separate neural network systems 40. The outputs of the separate network systems 40 are then inputted into the central data processing device 3. The central data processing device 3 uses the interface devices 10 (See Figure

1B) to convert the outputs of the separate network systems 40 into a usable form, and then stores all the converted outputs in its measurement data memory bank 8, further processes the outputs into parameter data before storage, or reports the outputs from the separate network systems 40.

In this third embodiment, the separate network systems 40 can be implemented as either computer(i.e., software)-generated or hard-wired systems. As computer-generated systems, the separate network systems 40 can be further implemented as separate computers or data processing devices, or as separate neural network systems 40 on the same computer or data processing device. Each of the measuring instruments 2 is designed to generate data for a plurality of parameters (i.e., $N \geq 3$), whereby their corresponding neural network systems 40 can generate the necessary architectures during training. Similarly, the manual input terminal 6 is used to input a plurality of parameter data so that its corresponding neural network system 40 can generate the necessary architecture during its training. Each of the measuring instruments inputs data 2 via an interface device 41 to a corresponding neural network system 40. The manual input terminal 6 is also connected via an interface device 41 to a corresponding neural network 40. In this embodiment, the interface device 41 converts the data from the measuring instruments 2 and the manual input terminal 6 into parameter data usable by the neural network systems 40. The interface device 41 can be implemented as either software or hardware equivalent to the devices implementing the interface devices 10 in the first and second embodiments of the present invention discussed above.

Fourth Embodiment

In a fourth embodiment of the present invention as shown in Figure 6, each of the measuring instruments 2 separately outputs measurement data 50. Each of the measuring instruments 2 represents an automated measuring device that is not connected to the central data processing device 3, but that is used to generate and output measurement data

50. The measurement data 50 from each of the instruments 2 is inputted through a manual input terminal 51 into the central data processing device 3. Manual measurements and testing 2a done using non-automated instruments and laboratory procedures to generate measurement data 50 can also be inputted into the central data processing device 3 using a manual input terminal 51.

The manual input terminals 51 can be implemented as terminals to the central data processing device 3 implemented as a mainframe computer, or as stand-alone personal computers communicating with the central data processing device 3 implemented as a network server. When implemented as stand-alone personal computers, the manual input terminals 51 after receiving the measurement data 50 can process it, such as by calculating other parameter data from the measurement data 50 or by converting it into a data format usable by either the central data processing device 3 or the neural network system 4. The manual input terminals 51 can even store the measurement data 50.

In the central data processing device 3, the measurement data 50 and other parameter data from the manual input terminals can be stored in the measurement data memory bank 8 or be further processed into a form usable by the neural network system 4 before storage. The neural network system 4 accesses the central data processing device 3 for all the parameter data needed. The neural network system 4 initiates its analysis and accesses the memory banks 8 of the central data processing device 3 based on a signal from the central data processing device 3, or from a user.

Fifth Embodiment

In a fifth embodiment of the present invention as shown in Figure 7A, each of the measuring instruments 2, representing an automated measuring device not connected to the central data processing device 3, separately outputs measurement data 60. The measurement data 60 from each of the measuring instruments 2 is inputted through a manual input terminal 61 into the neural network system 4. Manual measurements and testing 2a done using non-automated instruments and laboratory procedures to generate

measurement data 60 can also be inputted into the neural network system 4 through a manual input terminal 61.

Like the fourth embodiment described above, the manual input terminals 61 can be implemented as terminals to the neural network system 4 implemented as a mainframe or stand-alone computer. Alternatively, the manual input terminals 61 can be implemented as stand-alone personal computers communicating with the neural network system 3. When implemented as stand-alone personal computers, the manual input terminals 61 after receiving the measurement data 60 can process it, such as by calculating other parameter data from the measurement data 60 or by converting it into a data format usable by the neural network system 4. The manual input terminals 61 can also store the measurement data 60.

The outputs generated by the neural network system 4 are inputted into the central data processing device 3 either manually using a separate manual input terminal connected to the central data processing device 3, or through an interface device between the computer or data processing device implementing the neural network system 4 and the central data processing system 3. The outputs of the neural network system 4 are outputted through the output device 5 connected to the central data processing device 3.

In a variation of this fifth embodiment, as shown in Figure 7B, the measuring instruments 2 and the manual input terminal 61 for the manual measurement and testing 2a are connected via interface devices 62 to the neural network system 4. Data from the measuring instruments 2 is therefore inputted directly into the neural network system 4, instead of through the manual input terminals 61. The interface devices 62 convert the data from the measuring instruments 2 into a form usable by the neural network system 4. The interface devices 62 can also be implemented as software or hardware equivalent to the devices used to implement the interface devices 10 in the first and second embodiments described above.

Sixth Embodiment

In a sixth embodiment of the present invention as shown in Figure 8, each of the measuring instruments 2, representing an automated measuring device not connected to the central data processing device 3, separately outputs measurement data 70. The measurement data 70 from each of the instruments 2 is inputted through a manual input terminal 71 into the neural network system 4. Manual measurements and testing 2a done using non-automated instruments and laboratory procedures to generate measurement data 70 can also be inputted into the neural network system 4 through a manual input terminal 71. The manual input terminals 71 process the measurement data 70. For example, after receiving the measurement data 70, the manual input terminals 71 can calculate other parameter data from the measurement data 70, and convert the data into a form usable by the neural network system 4. The outputs generated by the neural network system 4 are outputted through the output device 5 connected to the computer or data processing device implementing the neural network system 4.

In a variation of this sixth embodiment, as shown in Figure 8B, the measuring instruments 2 and the manual input terminal 71 for the manual measurement and testing 2a are connected via interface devices 72 to the neural network system 4. Data from the measuring instruments 2 is therefore inputted directly into the neural network system 4, instead of through the manual input terminals 71. The interface devices 72 convert the data from the measuring instruments 2 into a form usable by the neural network system 4. As with the prior embodiments, the interface devices 72 can be implemented as software or hardware equivalent to the devices used to implement the interface devices 10 in the first and second embodiments described above.

Modifications and variations of the above-described embodiments of the present invention are possible, as appreciated by those skilled in the art in light of the above teachings. For example, the output device 5 of the invention can be embodied in a device for translating the output of the neural network system 4 into control signals. Such control signals can include signals for controlling the measuring instruments 2 to repeat

the tests or initiate new tests, signals controlling equipment monitoring a patient to output current readings or to change their current monitoring settings, signals controlling medication-administering equipment, or signals controlling communicating with diagnostic systems for generating treatment procedures for a patient.

The system of the present invention is applicable to different fields of endeavor outside of the medical field as described above. For example, the system of the invention would be applicable to the field of automated manufacturing machines. The system may be used to monitor various machines in an automated assembly line, or even to monitor a device or chemical being manufactured. During the course of operation of a machine or manufacturing system, parameter data is measured or taken to monitor the machine and thereby maintain the machine at optimum performance. When monitoring a device or chemical being manufactured, as the part or system progresses through its manufacture, parameter data is measured or taken to insure that the device or chemical is being assembled properly.

Other examples of where the system of the present invention may be applied include the use of the system to monitor the operation of a car, aircraft, ships, robots or spacecraft over the lifetime of the object. Parameter data can be measured or taken on a periodic basis to monitor the operation and performance of the object.

It is therefore to be understood that, within the scope of the appended claims and their equivalents, the invention may be practiced otherwise than as specifically described.

TABLE 1

Network Version	TSH	T4	Free T4	T3	T3 Uptake	FTI
1	Used	Used	Used	Used	Used	Used
2	*	Used	Used	Used	Used	Used
3	Used	*	Used	Used	Used	Used
4	Used	Used	*	Used	Used	Used
5	Used	Used	Used	*	Used	Used
6	Used	Used	Used	Used	*	Used
7	Used	Used	Used	Used	Used	*
8	*	*	Used	Used	Used	Used
9	*	Used	*	Used	Used	Used
10	*	Used	Used	*	Used	Used

Used = Parameter is used by Network Version

* = Parameter not used by Network Version

TABLE 2

PATIENT #	TSH	T4	T3UP	T3	FREE T4	FT1	DIAG.	ERROR/ NOT
1	1.2	6.0	31.4	152	1.0	1.9	EUTHYROID	CORRECT
2	0.1	15.0	27.9	179	3.4	4.2	HYPERTHYROID	CORRECT
3	<0.1	13.9	31.8	232	3.2	4.4	HYPERTHYROID	CORRECT
4	<0.1	14.9	33.8	334	3.0	5.0	HYPERTHYROID	CORRECT
5	1.2	6.4	27.7	177	1.0	1.8	EUTHYROID	CORRECT
6	1.8	5.9	28.5	163	1.0	1.8	EUTHYROID	CORRECT
7	5.6	8.6	28.4	187	1.0	2.4	EUTHYROID	CORRECT
8	0.1	16.3	25.6	251	3.3	4.2	HYPERTHYROID	CORRECT
9	1.1	9.2	27.4	160	1.3	2.5	EUTHYROID	CORRECT
10	0.9	6.7	32.7	157	1.1	2.2	EUTHYROID	CORRECT
11	0.4	9.2	31.7	160	1.4	2.9	EUTHYROID	CORRECT
12	2.2	9.1	28.5	129	1.7	2.6	EUTHYROID	CORRECT
13	1.2	8.9	28.1	123	1.5	2.5	EUTHYROID	CORRECT
14	21.6	3.1	32.9	112	0.2	1.0	HYPOTHYROID	CORRECT
15	22.1	3.0	32.9	111	0.1	1.0	HYPOTHYROID	CORRECT
16	22.4	2.9	32.0	111	0.3	0.9	HYPOTHYROID	CORRECT
17	23.1	2.5	32.6	101	0.1	0.8	HYPERTHYROID	CORRECT
18	<0.1	17.9	33.9	217	2.8	5.9	HYPERTHYROID	CORRECT
19	<0.1	15.7	36.0	307	3.5	5.7	HYPERTHYROID	CORRECT

TABLE 2 (Continued)

PATIENT #	TSH	T4	T3UP	T3	FREE T4	FTI	DIAG.	ERROR/ NOT
20	<0.1	12.8	32.3	174	2.5	4.1	HYPERTHYROID	CORRECT
21	<0.1	13.6	32.5	199	2.6	4.4	HYPERTHYROID	CORRECT
22	72.0	1.3	25.1	75	0.2	0.3	HYPOTHYROID	CORRECT
23	75.0	1.5	25.2	77	0.3	0.4	HYPOTHYROID	CORRECT
24	77.0	1.5	25.2	77	0.1	0.4	HYPOTHYROID	CORRECT
25	80.0	1.9	25.6	88	0.2	0.5	HYPOTHYROID	CORRECT
26	5.6	8.6	28.4	251	1.0	2.4	ERROR	ERROR
27	21.6	3.1	32.9	334	0.2	1.0	ERROR	ERROR
28	0.1	1.3	25.6	39	3.3	42	ERROR	ERROR
29	1.1	9.2	27.4	39	1.3	2.5	ERROR	ERROR
30	0.9	6.7	32.7	157	3.2	2.1	ERROR	ERROR
31	72.0	1.3	25.1	75	3.2	0.3	ERROR	ERROR
32	2.3	7.0	29.8	142	0.3	2.1	ERROR	ERROR
33	<0.1	13.9	31.8	232	0.3	4.4	ERROR	ERROR
34	72.0	0.0	25.1	75	0.2	0.0	ERROR	ERROR
35	<0.1	17.9	33.9	0	2.8	5.9	ERROR	ERROR
36	1.3	7.9	34.1	143	0.0	2.7	ERROR	ERROR
37	2.3	7.0	29.8	345	0.3	2.1	ERROR	ERROR
38	67	1	23.3	300	0.3	0.2	ERROR	ERROR
39	0.4	160.0	31.7	9.2	1.4	2.9	ERROR	ERROR

TABLE 2 (Continued)

PATIENT #	TSH	T4	T3UP	T3	FREE T4	FT1	DIAG.	ERROR/ NOT
40	<0.1	232.0	31.8	232	13.6	4.4	ERROR	ERROR
41	22.1	111.0	32.9	3	0.1	1.0	ERROR	ERROR
42	0.0	16.3	25.6	39	3.3	4.2	ERROR	ERROR
43	5.5	8.5	28.5	253	1.0	2.4	ERROR	ERROR
44	21.7	3.0	33.1	336	0.2	1.0	ERROR	ERROR
45	<0.1	16.2	25.7	39.1	3.3	4.2	ERROR	ERROR
46	1.0	9.4	28.2	39	1.3	2.7	ERROR	ERROR
47	73.0	1.2	25.1	76	3.9	0.3	ERROR	ERROR
48	72.0	0.1	25.1	175	3.8	0.0	ERROR	ERROR
49	<0.1	14.6	31.8	232	0.3	4.4	ERROR	ERROR
50	<0.1	15.6	26.2	39.1	3.3	4.1	ERROR	ERROR

WHAT IS CLAIMED IS:

1. A method for analyzing measurements and test results on an object being examined, comprising the steps of:

providing a neural network system formed to diagnose a condition of the object being examined, and to recognize errors in measurement data;

obtaining measurement data on said object being examined;

converting said measurement data into parameter data for said neural network system;

inputting said parameter data into a neural network system for analysis;

determining via said neural network system whether an error exists in said parameter data;

outputting an error indication when an error does exist in said parameter data;

diagnosing via said neural network system said condition of said object based on said parameter data when error does not exist in said parameter data; and

outputting an analysis of said condition of said object.

2. A method according to claim 1, wherein said step of providing measurement data includes the steps of using at least one measuring instrument to generate said measurement data.

3. A method according to claim 1, wherein said step of providing a neural network system includes the step of providing a plurality of neural networks to comprise said neural network system.

4. A method according to claim 1, further comprising the steps of:

analyzing said parameter data via said neural network system when error does exist therein; and

identifying a portion of said parameter data as being the cause of error in said parameter data.

5. A method according to claim 3, further comprising the steps of:

analyzing said parameter data via select ones of said plurality of neural networks when error does exist therein; and

identifying a portion of said parameter data as being the cause of error in said parameter data.

6. A method according to claim 3, wherein said step of inputting said parameter data into said neural network system for analysis includes inputting said parameter data into select ones of said plurality of neural networks.

7. A method for analyzing measurements and test results on an object being examined, comprising the steps of:

conducting measurements on said object being examined;

generating measurement data based on said measurements;

converting said measurement data into parameter data for said neural network system;

inputting said parameter data into a neural network system formed to diagnose a condition of the object being examined, and to recognize errors in measurement data;

determining via said neural network system whether an error exists in said parameter data;

outputting an error indication when an error does exist in said parameter data;

diagnosing via said neural network system said condition of said object based on said parameter data when error does not exist in said parameter data; and

outputting an analysis of said condition of said object.

8. A method according to claim 7, wherein said step of conducting measurements on said object includes the steps of using at least one measuring instrument to generate said measurement data.

9. A method according to claim 7, further comprising the steps of:

analyzing said parameter data for determining the cause of the error;

inputting said parameter data into a plurality of neural networks in said neural network system;

determining the cause of error in said parameter data based on outputs from each of said plurality of neural networks; and

identifying a portion of said parameter data as being the cause of error in said parameter data.

10. A method according to claim 9, wherein said step of inputting said parameter data into said plurality of neural networks in said neural network system includes inputting said parameter data into select ones of said plurality of neural networks.

11. A system for analyzing measurements and test results on an object being examined, comprising:

a neural network system for diagnosing a condition of the object, said neural network system having means for recognizing error in parameter data inputted thereinto;

means for generating measurement data on the object;

means for interfacing said measuring instrument with said neural network system, said interfacing means including means for converting said measurement data into parameter data for said neural network system; and

means for outputting output signals from said neural network system, said output signals being formed to indicate at least one of the existence of an error in said parameter data and the condition of said object based on said parameter data.

12. A system according to claim 11, wherein said neural network system further includes means for analyzing said parameter data when error exists in said parameter data,

a plurality of neural networks, each of said plurality of networks being formed for diagnosing a condition of the object for recognizing error in a subset of said parameter data inputted thereinto, and

means for determining what portion of said parameter is the cause of error based on outputs of each of said plurality of neural networks.

13. A system according to claim 11, wherein said means for generating measurement data includes at least one measuring instrument.

14. A neural network system for analyzing measurements and test results on an object being examined, comprising:

neural network means for diagnosing a condition of the object, said neural network means including means for recognizing error in parameter data inputted thereinto;

means for generating measurement data on the object, said generating means including at least one measuring device; and

means for converting said measurement data into a plurality of parameter data for said neural network means, said neural network means further including means for generating signals indicating at least one of a diagnosis of said object and the existence of error in said plurality of parameter data inputted thereinto.

15. A neural network system according to claim 14, wherein said neural network means comprises means for analyzing said parameter data when error exists in said parameter data,

a plurality of neural networks each formed to analyze a subset of said plurality of parameter data, each of said plurality of neural networks being further formed for diagnosing a condition of said object, and for recognizing error in said subset of said plurality of parameter data inputted thereinto, and

means for determining which of said plurality of parameter data is the cause of error based on outputs from each of said plurality of neural networks.

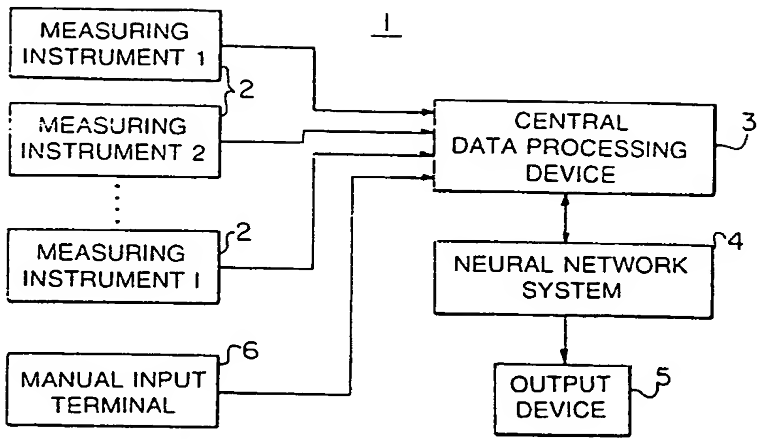


FIG. 1A

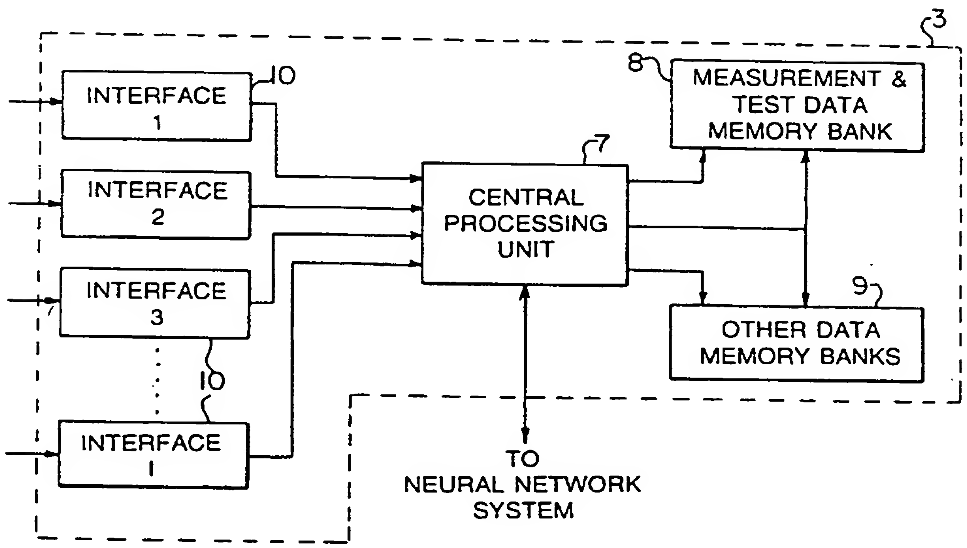


FIG. 1B

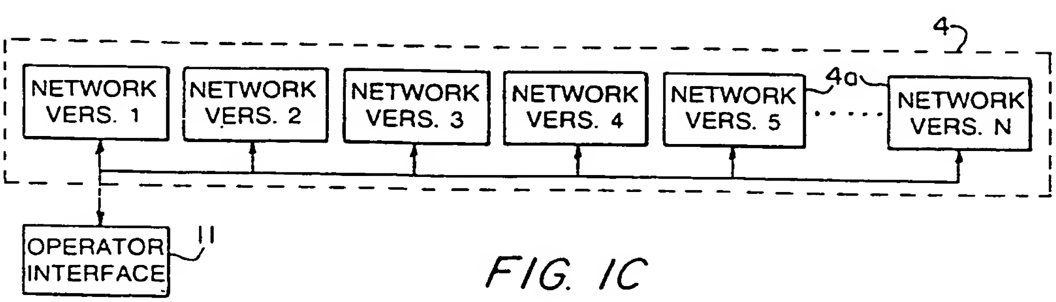


FIG. 1C

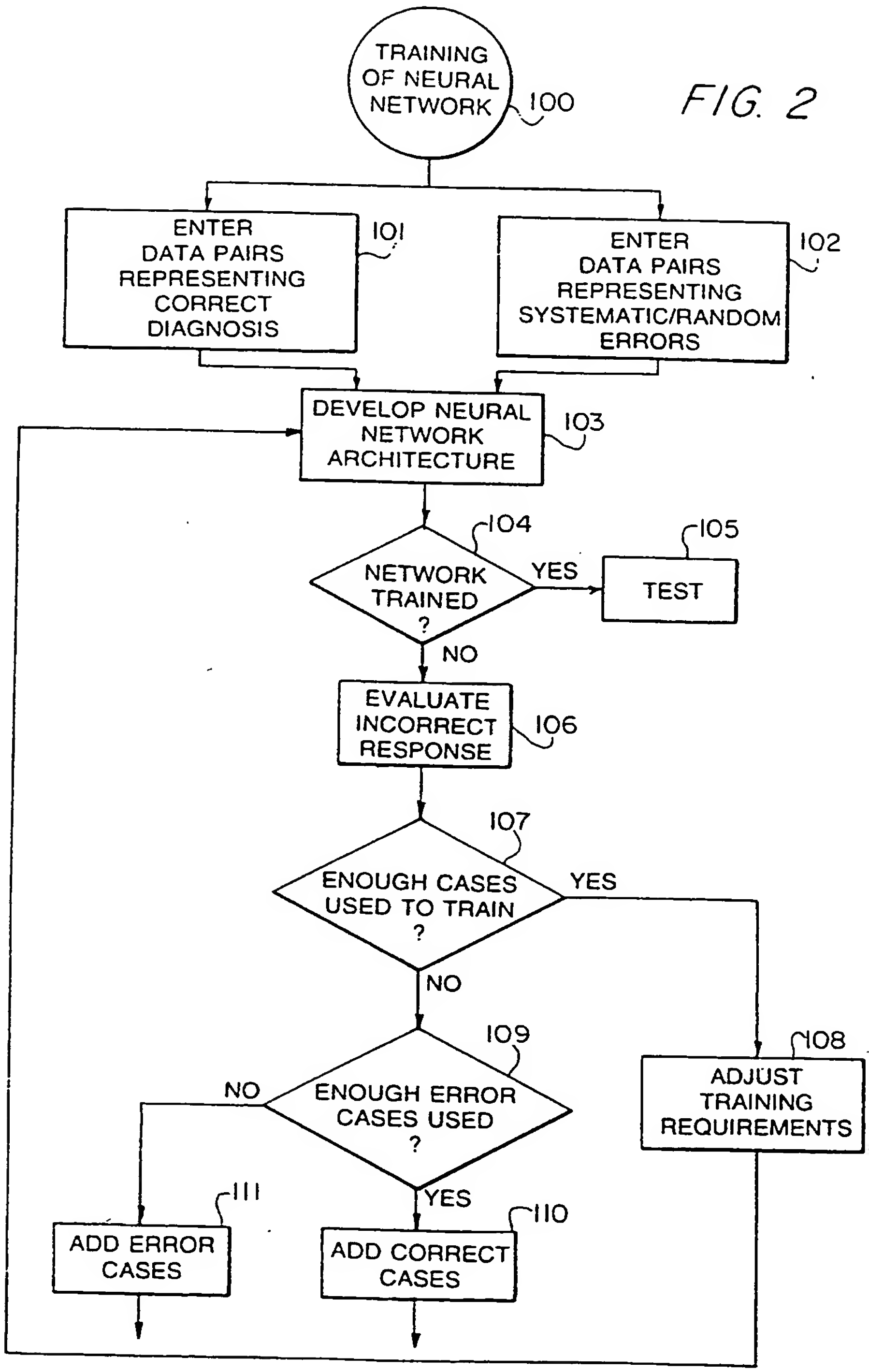

TRAINING OF NEURAL NETWORK
100
ENTER DATA PAIRS REPRESENTING CORRECT DIAGNOSIS
101
ENTER DATA PAIRS REPRESENTING SYSTEMATIC/RANDOM ERRORS
102
DEVELOP NEURAL NETWORK ARCHITECTURE
103
104
NETWORK TRAINED ?
YES
105
TEST
NO
EVALUATE INCORRECT RESPONSE
106
107
ENOUGH CASES USED TO TRAIN ?
YES
NO
109
ENOUGH ERROR CASES USED ?
NO
YES
108
ADJUST TRAINING REQUIREMENTS
111
ADD ERROR CASES
110
ADD CORRECT CASES

FIG. 2

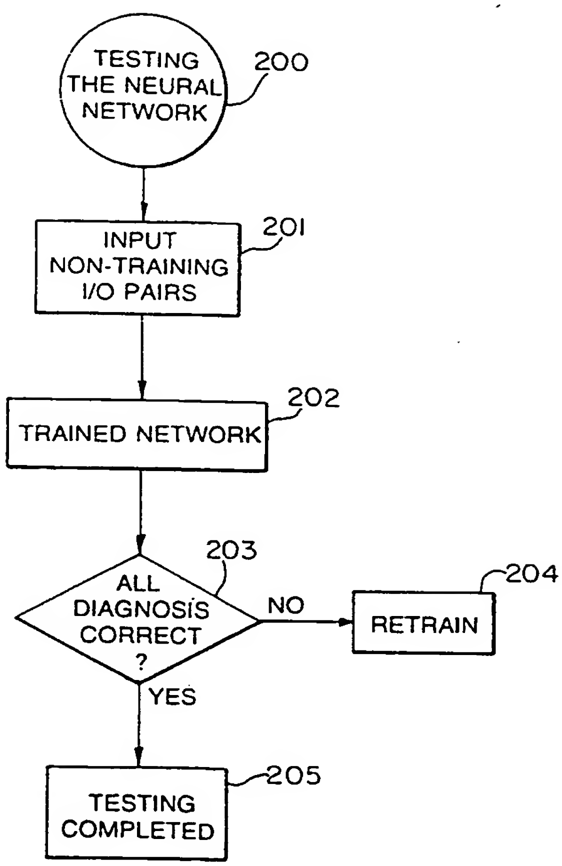

TESTING THE NEURAL NETWORK
200
INPUT NON-TRAINING I/O PAIRS
201
TRAINED NETWORK
202
ALL DIAGNOSIS CORRECT ?
203
NO
RETRAIN
204
YES
TESTING COMPLETED
205

FIG. 3

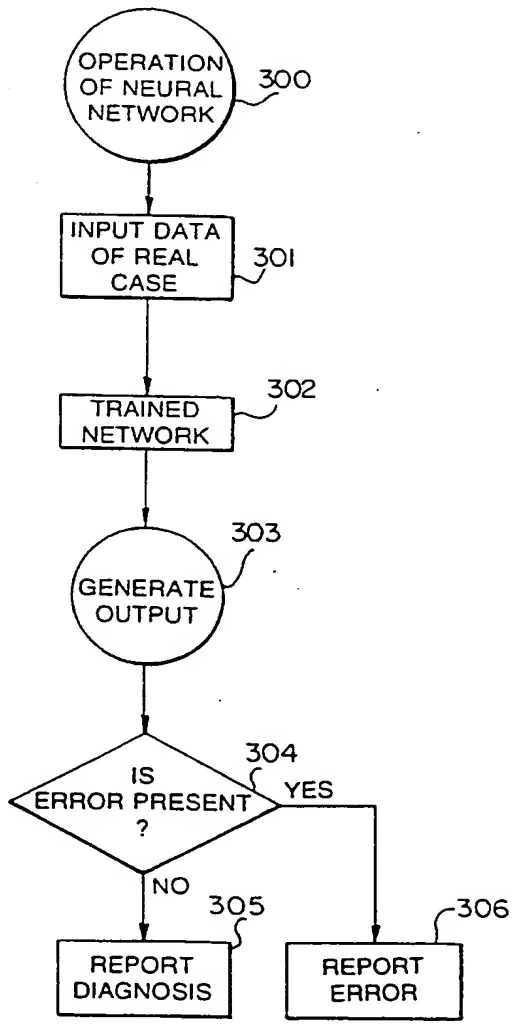

OPERATION OF NEURAL NETWORK
300
INPUT DATA OF REAL CASE
301
TRAINED NETWORK
302
GENERATE OUTPUT
303
IS ERROR PRESENT ?
304
YES
NO
305
306
REPORT DIAGNOSIS
REPORT ERROR

FIG. 4A

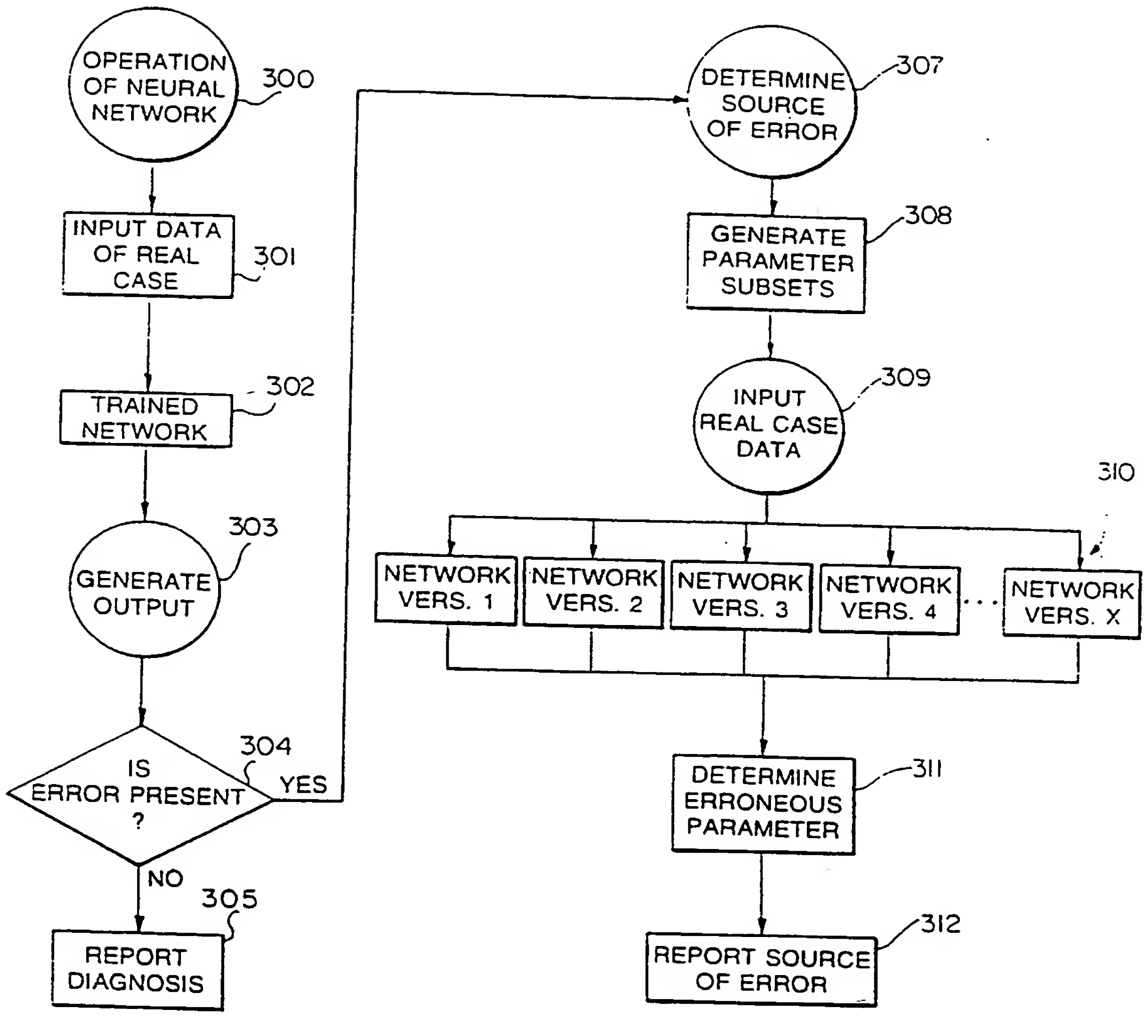

OPERATION OF NEURAL NETWORK
300
INPUT DATA OF REAL CASE
301
TRAINED NETWORK
302
GENERATE OUTPUT
303
IS ERROR PRESENT ?
304
YES
NO
REPORT DIAGNOSIS
305
DETERMINE SOURCE OF ERROR
307
GENERATE PARAMETER SUBSETS
308
INPUT REAL CASE DATA
309
310
NETWORK VERS. 1
NETWORK VERS. 2
NETWORK VERS. 3
NETWORK VERS. 4
NETWORK VERS. X
DETERMINE ERRONEOUS PARAMETER
311
REPORT SOURCE OF ERROR
312

FIG. 4B

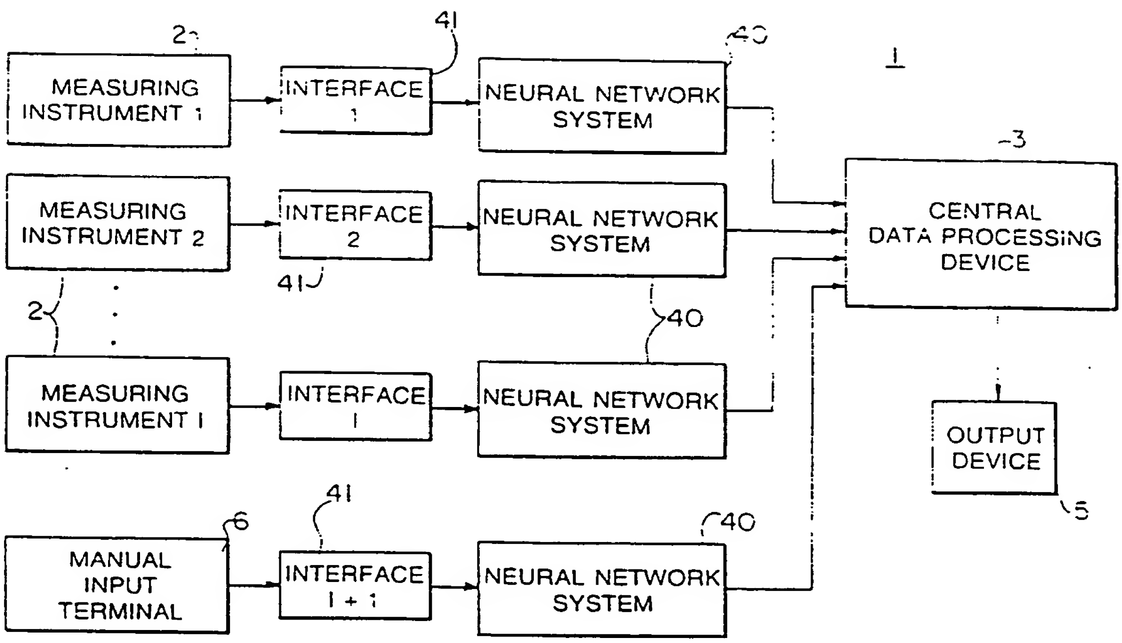
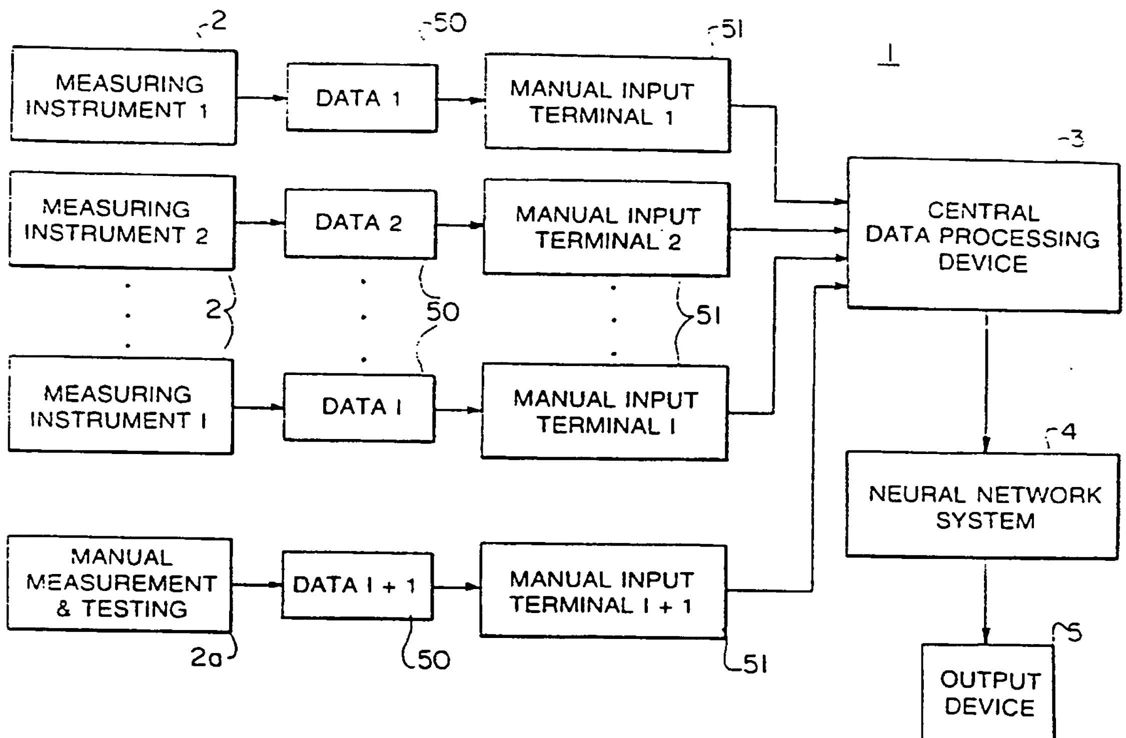

2
41
40
1
MEASURING INSTRUMENT 1
INTERFACE 1
NEURAL NETWORK SYSTEM
3
CENTRAL DATA PROCESSING DEVICE
MEASURING INSTRUMENT 2
INTERFACE 2
NEURAL NETWORK SYSTEM
41
2
40
MEASURING INSTRUMENT I
INTERFACE I
NEURAL NETWORK SYSTEM
OUTPUT DEVICE
5
41
6
40
MANUAL INPUT TERMINAL
INTERFACE I + 1
NEURAL NETWORK SYSTEM

FIG. 5



2
50
51
1
MEASURING INSTRUMENT 1
DATA 1
MANUAL INPUT TERMINAL 1
3
CENTRAL DATA PROCESSING DEVICE
MEASURING INSTRUMENT 2
DATA 2
MANUAL INPUT TERMINAL 2
2
50
51
MEASURING INSTRUMENT I
DATA I
MANUAL INPUT TERMINAL I
4
NEURAL NETWORK SYSTEM
MANUAL MEASUREMENT & TESTING
DATA I + 1
MANUAL INPUT TERMINAL I + 1
2a
50
51
5
OUTPUT DEVICE

FIG. 6

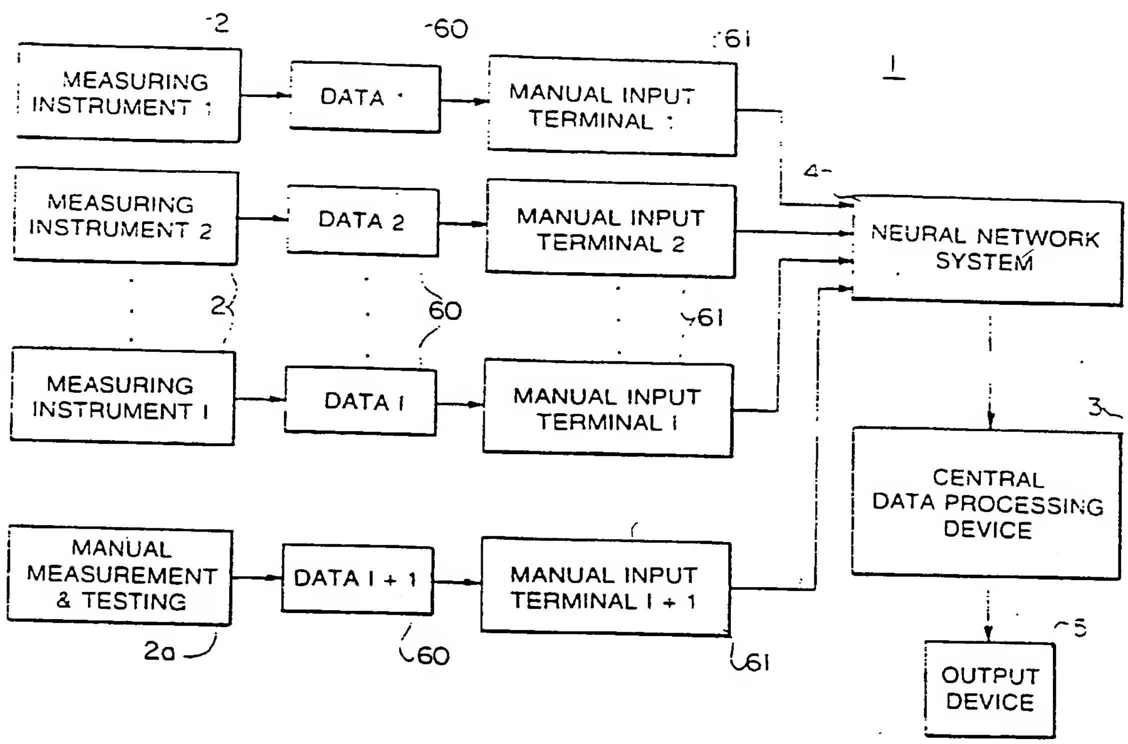

2
60
61
1
MEASURING INSTRUMENT 1
DATA 1
MANUAL INPUT TERMINAL 1
4
MEASURING INSTRUMENT 2
DATA 2
MANUAL INPUT TERMINAL 2
NEURAL NETWORK SYSTEM
2
60
61
MEASURING INSTRUMENT I
DATA I
MANUAL INPUT TERMINAL I
3
CENTRAL DATA PROCESSING DEVICE
MANUAL MEASUREMENT & TESTING
DATA I + 1
MANUAL INPUT TERMINAL I + 1
2a
60
61
5
OUTPUT DEVICE

FIG. 7A

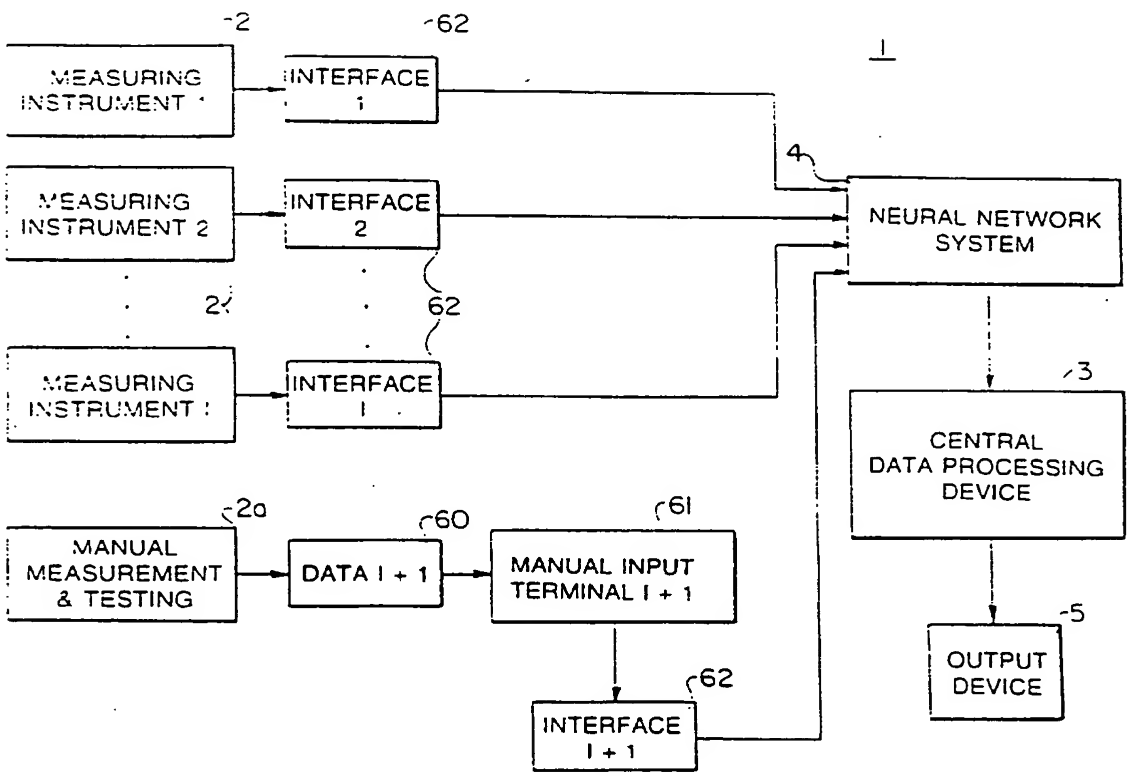

2
62
1
MEASURING INSTRUMENT 1
INTERFACE 1
4
MEASURING INSTRUMENT 2
INTERFACE 2
NEURAL NETWORK SYSTEM
2
62
MEASURING INSTRUMENT I
INTERFACE I
3
CENTRAL DATA PROCESSING DEVICE
2a
60
61
MANUAL MEASUREMENT & TESTING
DATA I + 1
MANUAL INPUT TERMINAL I + 1
5
OUTPUT DEVICE
62
INTERFACE I + 1

FIG. 7B

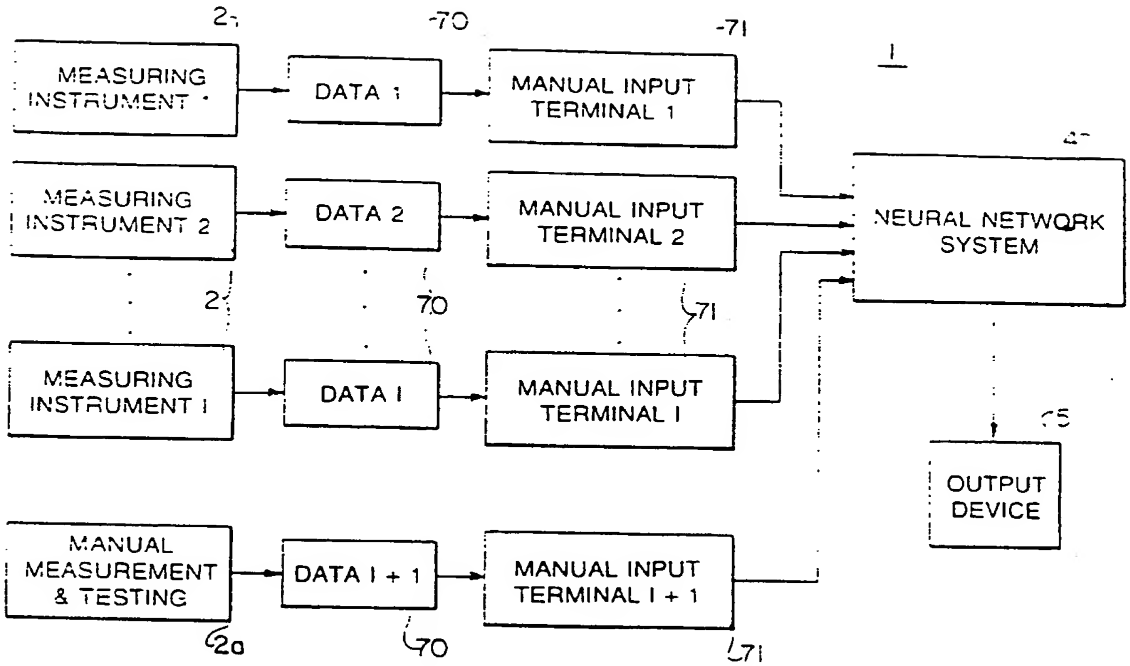

MEASURING INSTRUMENT 1
DATA 1
MANUAL INPUT TERMINAL 1
MEASURING INSTRUMENT 2
DATA 2
MANUAL INPUT TERMINAL 2
MEASURING INSTRUMENT I
DATA I
MANUAL INPUT TERMINAL I
NEURAL NETWORK SYSTEM
OUTPUT DEVICE
MANUAL MEASUREMENT & TESTING
DATA I + 1
MANUAL INPUT TERMINAL I + 1
70
71
2a
1

FIG. 8A

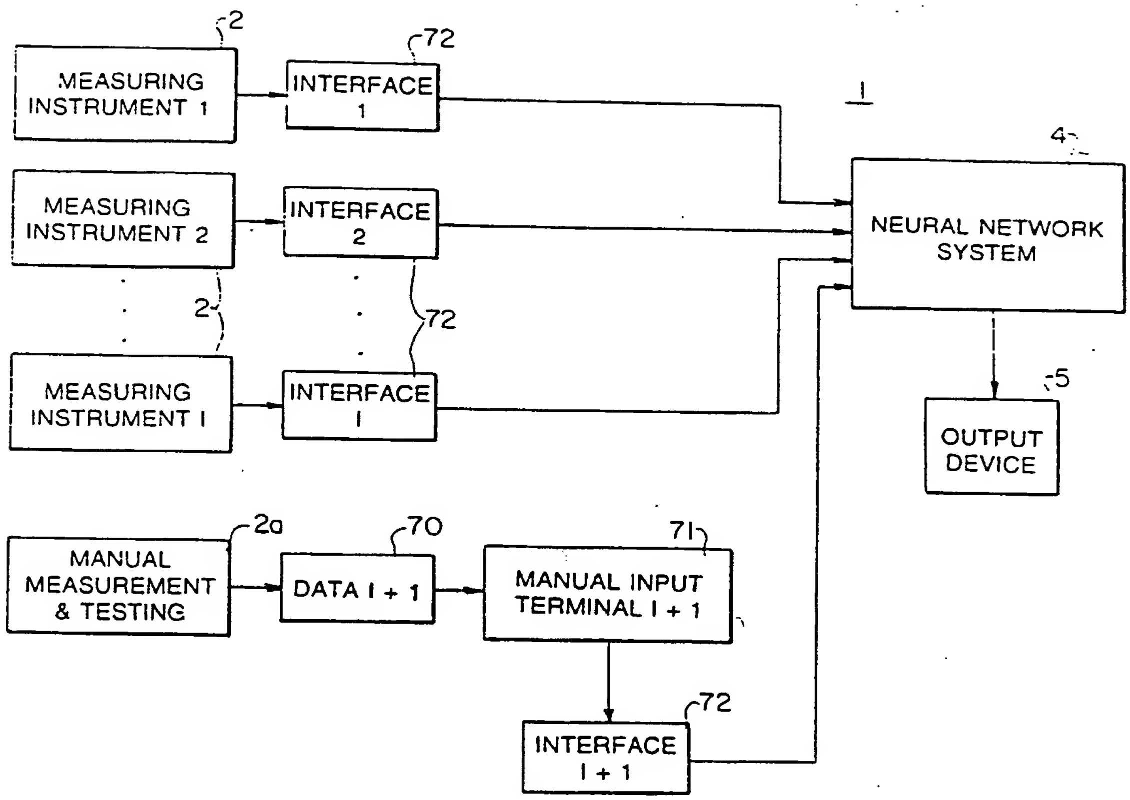

2
MEASURING INSTRUMENT 1
72
INTERFACE 1
MEASURING INSTRUMENT 2
INTERFACE 2
2
72
MEASURING INSTRUMENT I
INTERFACE I
1
4
NEURAL NETWORK SYSTEM
5
OUTPUT DEVICE
2a
MANUAL MEASUREMENT & TESTING
70
DATA I + 1
71
MANUAL INPUT TERMINAL I + 1
72
INTERFACE I + 1

FIG. 8B

INTERNATIONAL SEARCH REPORT

International application No.
PCT/US96/13498

A. CLASSIFICATION OF SUBJECT MATTER

IPC(6) :G06F 15/18
US CL : 395/22
According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

U.S. : 395/22

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

APS, PROQUEST
S NEURAL NET? AND MEASURE? DATA AND ERROR

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	US, A, 5,349,646 (FURUTA) 20 SEPTEMBER 1994, FIG 2.	1-15
Y	US,A, 5,303,328 (MASUI ET AL.) 12 APRIL 1994, FIG 1A & 1B.	1-15
Y	US, A, 5,285,523 (TAKAHASHI) 08 FEBRUARY 1994, SEE FIG 1.	1-15

☐ Further documents are listed in the continuation of Box C. ☐ See patent family annex.

* Special categories of cited documents:

"A" document defining the general state of the art which is not considered to be part of particular relevance

"E" earlier document published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
26 SEPTEMBER 1996	31 OCT 1996

Name and mailing address of the ISA/US Commissioner of Patents and Trademarks Box PCT Washington, D.C. 20231	Authorized officer SANJIV SHAH
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